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Benchmarking AI-Based Precision Farming Models for Agricultural Decision Making Using FAOSTAT Data

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Abstract – This paper evaluates the AI-based Precision Farming (PF) models with the benchmark data set of FAOSTAT combined with simulated IoT sensor data from 30 borehole and field variables. Feedforward Artificial Neural Network (ANN), Random Forest (RF), k-Nearest Neighbors (kNN), Naive Bayes (NB), and the proposed hybrid Graph Neural Network (GNN) machine learning algorithms were trained and tested using an 80:20 data split. To achieve this, we used measures of evaluation, which included integrated recall, execution time, and precision. From the information gathered regarding the experiment, ANN achieved an accuracy of 98.65, the highest precision of 98.32, and the best recall rate of 97.65, which were the best measurement of the models. Integration of the three (i.e., soil moisture, temperature, and humidity) IoT-enabled sensors improved the environmental realism and generalizability of the model, enabling the real-time monitoring and predictive analytics of the crops.

Keywords – Precision Farming, Artificial Intelligence, IoT Sensors, Machine Learning, Graph Neural Networks, Crop Yield Prediction, FAOSTAT Dataset.

I. INTRODUCTION

The use of Artificial Intelligence (AI) would facilitate the task of resource distribution and reduce labor and productivity issues in the agricultural sector. The possibilities of AI make it possible to turn smart farming into an indispensable need for effective distribution of resources, which is paramount to the achievement of sustainable food production [1]. The implementation of AI solutions to monitor and recognize crop disease would assist farmers in strengthening production by identifying the disease in the early stages. These systems receive and interpret real-time sensor images and historical images and meteorological images to offer guidance by forecasting the critical decisions to safeguard the quality and safety of crop harvests. Moreover, the AI application within the operational supply chain addresses the problem of resource waste.

The AI projects revolving around food waste management might play a vital role in reducing food waste considerably by optimizing inventories, predictive data on food spoilage, and streamlining logistics. It is particularly helpful to the small-scale farmers who are usually hampered by access to markets. However, to achieve these benefits, numerous serious obstacles need to be overcome, including high costs of implementation, insufficient digital infrastructure and the unawareness of farmers regarding the potentially beneficial aspects of AI. These barriers are also ubiquitous in the Malaysian agricultural industry and represent a significant challenge to the widespread adoption of AI. The Malaysian government has come to understand the necessity of digital transformation in the farming sector by creating initiatives like the National Agrofood Policy 2.0 [2].

Twenty-first-century agriculture is largely data-driven. Statistical approaches and data analytics characterize the basis of the perception of agricultural performances, soil health conditions, insect phenomenon and behavior on the market. Agriculture contributes approximately 4% of the total GDP in the globe and absorbs approximately 27% of the total labor force, and thus it must be effective and productive. According to the FAO (Food and Agriculture Organization), the world food production will need to grow by approximately 60 percent by 2050 to handle the needs of the population that is estimated to reach 9.71 billion [3]. This dimension of production involves applying statistical tools to determine trends in order to distribute resources and make predictions about the outcome in agriculture more effectively. By applying analytics to data collected at weather stations, remote sensing satellites and IoT devices, farmers and scientists can improve decision-making, minimize waste and aid in supplementing the harvest in a sustainable manner.

Benchmarking can aid farmers in enhancing their sustainability and productivity outcomes. Farm benchmarking helps farmers to assess their performance against their peers, learn from others and identify measures that need to be taken. Benchmarking is dependent upon an exchange of data. In more than 80% of member states in the EU, benchmarks are frequently discussed either individually between a farmer and their advisors or in peer groups [4]. The development of the readiness and technical abilities to easily share data from farm-level systems between networks will foster more involvement in benchmarking. This will improve the dataset, thus increasing the precision and pertinence of benchmarking.

The Crop Weed Recognition Dataset (CWD30) in [5] refers to a large-scale image dataset of various crop and weed classes in different field conditions. Based on this, the current research combines the FAOSTAT benchmark data with the artificial data from the IoT sensor to record environmental dynamics like soil moisture, temperature, and humidity. The resulting multimodal data fusion indeed increases the realism and generalizability of AI-based precision agriculture models, while also enabling effective performance assessment in heterogeneous agricultural environments.

The remaining sections of this study have been organized in the following manner: Section II explains how GPS and remote sensing, IoT and GIS, ML and AI, fertilization or pesticide application technology, regenerative agriculture technology and CSA technology can piece together if used in conjunction. Section III describes our methodology, which includes our research framework, data source, model development, and experimental setup. A discussion of our findings is presented in Section IV. Finally, Section V sums up our work, pointing to the use of AI data in PA systems to improve efficiency and predictability.

II. THE ADOPTION OF PA

PA has become more significant to the world as countries across the globe have need both secure food security and sustainable agricultural and agricultural development. Precision in agriculture increases the volume and quality of agricultural products and also desecrates environmental conditions [6]. From a global perspective, the practice of precision agriculture includes four components: spatial placement, data collecting, data analysis, and precision processing. This framework makes it easier to collect the data, support decision-making, and control the rates dynamically.

GPS and Remote Sensing

The U.S. Department of Defense manages and develops the GPS satellite network [7]. The geodetic position of satellites in the earth-orbiting GPS constellation conveys their time and location precisely to ground receivers. The receiver units on the ground may also be simultaneously receiving the location data from multiple satellites at the same timeframe and thus identifying their accurate location. This data is delivered instantly; that is, there is ongoing delivery of positional information that is directed toward movement. Possessing accurate position data at all times allows the mapping of measurements of the crop, soil and water.

Remote sensing imagery of crops and soil is evaluated and then uploaded to the GIS database. The agriculture field widely uses three types of remote sensing data sources: satellite sensors, airborne sensors, and local sensors. Proximal hand-held sensors are largely employed for fundamental research work, where collected information from the sensors is used to understand the correlation between biophysical parameters and spectral behavior of crops exposed to some stressor (nutritional, temperature, or hydric).

IoT and GIS

IoT and GIS evaluate data gathered through remote sensing and GPS and enable real-time surveillance of agricultural land and the establishment of a repository of spatial data to support precision control. IoT utilizes sensor systems to uninterruptedly monitor information on light intensity, soil moisture levels, temperature, and other parameters and provides farmers with a rich source of data to make decisions according to ecological conditions. Big data analytics helps enhance this process by evaluating data volumes and identifying patterns and trends, which may help guide agricultural operations.

GIS technology is a specialized technology that concerns the integration and analysis of the spatial data and is used to visualize and analyze the relations, time-related changes and geo-pattern in a more detailed way. The use of GIS technology to study agricultural changes and deliver information used in forecasting early warning and farm output was undertaken by Mathenge, Sonneveld and Broerse [8]. They analyzed phosphorus in the soil by GIS, predicted the spatial distribution of organic phosphorus in agricultural soils in Southwestern Australia, and analyzed conditions of phosphorus deficiency.

ML and AI

ML and AI technologies contribute to precision agriculture by implementing a set of sophisticated algorithms that allow analyzing all agricultural data. ML uses superior techniques to predict agricultural data. Machine-learning models can be used to identify trends and correlations in unanalyzable data. The models are also useful in making better predictions about the pest problems, disease outbreaks and loss of crop yield. Algorithms are dynamic and adjust to new developments in the agricultural sector as they are supplied with new data. This helps farmers estimate changes when making agricultural decisions. Probably, the random forest regression algorithm will enable a scientist to forecast a crop yield using a multisource satellite image, and with a probability that could explain the meaning of crop yield prediction [9].

Agriculturalists and farmers are capitalizing on AI to apply irreversible techniques to produce more food. It does this by advanced algorithms and models that help with evolving decisions. AI models are formulated to evaluate data from multiple sources, such as satellite images, IoT sensors, and traditional agricultural records (e.g., past weather data). By taking in this information, it lets farmers plan scientifically regarding their goals and conditions. With predictive analytics, it will be able to suggest the ideal time to plant, crop rotations and pest protection methods. Moreover, AI techniques offer information about consumer tastes and market trends, allowing farmers to adjust and enhance their production techniques to match consumer demand.

Pesticide and Fertilization Application Technology

PA requires correct irrigation and fertilization according to the conditions in which farmland grows. Conventional irrigation and fertilization techniques often result in contamination and waste, but pesticide application and precision fertilization technology are proficient ways of mitigating this problem. It specifically uses pesticides according to their characteristics and presence of targets and therefore reduces the accumulation of pesticides in non-target areas.

Consequently, precision technology for pesticide application improves results, saves expenses, avoids environmental contamination, and enhances the disease susceptibility of crops as well as product quality. Marcal and Cunha designed a system to measure the application rate of granular fertilizer based on image technology. They developed a variable-rate fertilizer system that automatically applies the correct amount of fertilizer to the crops. In a study done by Yu et al. [10], an online testing method was developed that measures the application degree of solid fertilizer in a drilling machine for seed fertilizer. It was determined that the application rates were accurately measured using this method.

The Technology of Regenerative Agriculture

In regenerative agriculture, soil is considered a living entity, and soil health is not just measured by its mineral content but also by the diverse ecosystem of microorganisms in the soil. Regenerative farming regenerates soil and builds rich, biodiverse soil, necessary to produce healthy food. Organic farming employs environmentally friendly farming/cultivation and grazing methods, which reduce degradation through the industrial and conventional systems of farming and assist in regenerating soil organic matter, in addition to restoring ecosystems. Amplifying the abundance of microbes is a significant feature of healthy, effective control of nutrients and moisture. Soil amendment with organic matter is getting popular because of numerous advantages such as improved soil health and higher water infiltration. Regenerative methods reduce the input of cost productions and increase significantly the production of the harvest crops, which makes production easier and cost-efficient. This method is considerate of the comfort of animals as this enhances the livestock productivity and quality [11].

CSA Technology

Climate-smart agriculture (CSA) practices and techniques incorporated into agriculture are providing new opportunities to achieve sustainability, productivity and climate resilience goals. Organizations throughout our world, including the FAO, the OECD, the European Union, the World Bank, and its major Green Deal and CAP (Common Agricultural Policy), furnish a framework for food frame transformation.

Notwithstanding the great benefits, there are still few and sporadic global implementations of Climate-Smart Agriculture (CSA). The change to CSA is an intricate, varied process stimulated by policy, institutional, social, technological, and socio-economic elements. Numerous publications propose that these changes necessitate coordination of methods for different stakeholders [12]. To enhance the shift to CSA, it is important to comprehend farmers' behavior not as an isolated action but in broader food systems that establish power imbalances and trade-offs.

III. METHODOLOGY

This paper will involve a systematic methodology in evaluating the efficacy of AI-assisted precision farming systems relying on the FAOSTAT benchmark dataset. In order to achieve accuracy, reproducibility and computational efficiency, the methodological process includes data acquisition, preprocessing, model development and comparative performance evaluation.

This procedure will be used to simulate a real-life scenario of precision agriculture as both benchmark data and IoT sensor data will be read so that the resulting changes in agricultural conditions can be rightly shown.

Research Framework and Workflow
The overall research direction is a sequence of steps beginning with data collection, preprocessing, model creation, evaluation, and training. All steps will aid in the creation of a data-based model on the topic of predictive analysis in precision farming. **Fig. 1** shows the research workflow, which outlines the logical process of information acquisition and the comparative evaluation of the classification models.

Data Source and Preprocessing
The primary material used in the research was the FAOSTAT benchmark data, available at the FAO at the UN see **Table 1**. It also provides the complete agricultural statistics of over 190 countries and gives details of crops yields, soil fertility, climatic conditions, fertilizer use and land use trends. To replicate variability and dynamics of the environment, researchers used MATLAB and Python to produce simulated data of the sensors of the IoT, such as soil moisture, temperature and humidity levels. The combination of the benchmark information with the IoT sensor information reinforced the applicability of this model to real-world precision farming scenarios.

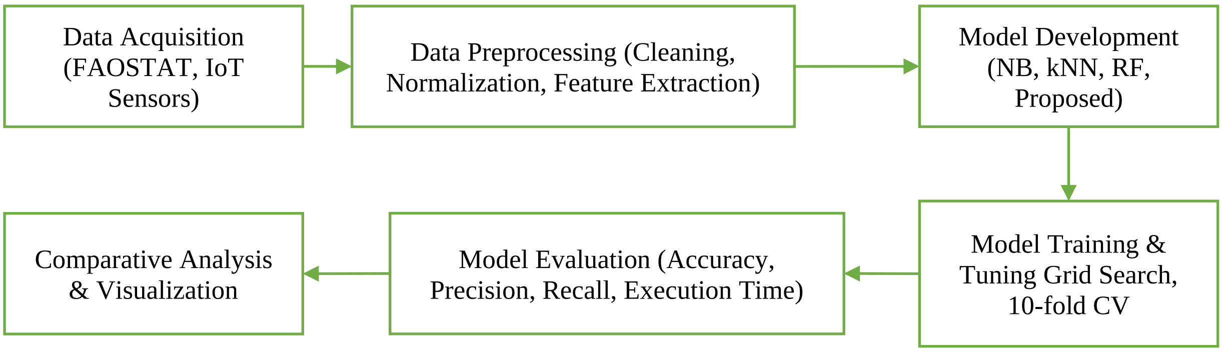

Fig 1. Artificial Intelligence-Based Precision Farming.

The preprocessing of data also involved cleaning to address missing and inconsistent values, followed by the average imputation of continuous variables and the most frequent category imputation. The min-max scaling method was used to normalize features through Eq. (1).

$$x' = \frac{x - x_{\min}}{x_{\max} - x_{\min}} \tag{1}$$

where x' signifies the normal value, and $x_{\max}$ and $x_{\min}$ are the maximum and minimum observed variable values, respectively. Categorical variables like region identifiers were coded by one-hot encoding so that it could be compatible with the ML algorithms. PCA was then used to decrease the dimensions and maximize the ability to compute. The last dataset was grouped into 20% testing and 80% training in order to make it able to evaluate without being biased.

Table 1. Summary of Variables in the Selected FAOSTAT Dataset

Variable	Description	Unit	Type	Source
Crop_Yield	Total yield of major crops	Tonnes/ha	Continuous	FAOSTAT
Fertilizer_Usage	Annual fertilizer consumption	kg/ha	Continuous	FAOSTAT
Soil_Organic_Content	Soil organic matter percentage	%	Continuous	FAOSTAT
Temperature	Average annual temperature	°C	Continuous	FAOSTAT/IoT
Humidity	Relative humidity	%	Continuous	IoT Sensor
Rainfall	Mean annual precipitation	mm	Continuous	FAOSTAT
Region	Geographic identifier	-	Categorical	FAOSTAT

Model Development and Mathematical Formulation
Four classification models were developed and compared in the study which include RF, kNN, NB, and a proposed hybrid model of Graph Neural Network (GNN) that combines the information of the IoT sensors. Both models were informed by the need to analyze and forecast the yield patterns of crops with regard to soil quality, environmental and input utilization.

The Naive Bayes classifier used a probabilistic strategy to determine the conditional probability after observing data. of a class C given an input vector $X = (x_1, x_2, \dots, x_n)$ as Eq. (2).

$$P(C \mid X) = \frac{P(C)\prod_{i=1}^{n} P(x_i|C)}{P(X)} \tag{2}$$

where $P(C)$ is the initial belief probability of the class, and $P(x_i \mid C)$ is the conditional probability of feature x_i. The kNN algorithm categorized samples using majority vote using the Euclidean distance measure in Eq. (3).

$$d(p,q) = \sqrt{\sum_{i=1}^{n}(p_i - q_i)^2} \tag{3}$$

and the category was set to the most frequent label among the k closest neighbor. RF as an ensemble learning approach utilized various decision trees and arrived at the result class by aggregation using majority, denoted by Eq. (4).

$$\hat{y} = \text{mode}\{T_1(X), T_2(X), \ldots, T_n(X) \tag{4}$$

The proposed GNN model provided an extension of the classic feature-based learning with the introduction of relational dependencies between environmental and agricultural factors. The propagation of the information using the graph layers was in the wake of the formulation depicted in Eq. (5).

$$H^{(l+1)} = \sigma\left(D^{-\frac{1}{2}}AD^{-\frac{1}{2}}H^{(l)}W^{(l)}\right) \tag{5}$$

with $H^{(l)}$ representing the data matrix at layer l, A representing the association matrix, D representing the diagonal degree matrix, $W^{(l)}$ representing the learnable weighted matrix and σ represents the ReLU activation function. This model architecture enabled the depiction of intricate interdependence among the soil, weather, and crop yield parameters, enhancing the accuracy and predictability of classification see **Table 2**.

Table 2. Setting of Model Parameters

Model	Key Parameters	Optimization Method	Implementation Tool
Naïve Bayes	Gaussian NB	None	Scikit-learn
kNN	$k = 7$, Distance=Euclidean	Grid Search	Scikit-learn
Random Forest	Trees=200, Depth=15	Randomized Search	Scikit-learn
Proposed GNN	Layers=3, Hidden Units=64	Adam Optimizer, $LR = 0.001$	PyTorch

Evaluation Metrics and Experimental Setup

The quantitative indicators such as accuracy, F1-score, recall, precision, and time to execute were employed as model performance evaluation. These measures were calculated based on the components of a confusion matrix based on Eq. (6).

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN}\ \text{Precision} = \frac{TP}{TP+FP}, \text{Recall} = \frac{TP}{TP+FN}\quad \text{F1-score} = 2 \times \frac{\text{Precision}\times\text{Recall}}{\text{Precision}+\text{Recall}} \tag{6}$$

where FN is false negative, FP is false positive, TN is true negative and TP is true positive. The $T_{\text{exec}} = T_{\text{train}} + T_{\text{predict}}$ formula was also used in determining the computational efficiency during the model training and AH stages.

The experimental workstation had 32GB of memory and is powered by NVIDIA RTX 3060 and Intel Core i7-12700H RAM and processor (2.7 GHz). All the algorithms were coded in Python 3.11 based on Scikit-learn, TensorFlow, and PyTorch platforms. We implemented hyperparameter tuning through grid search optimization with ten-fold cross-validation for enhancing the reliability and robustness of the models see **Table 3**.

Table 3. Setting Up of the Experimental Environment

Component	Specification
CPU	Intel Core i7-12700H, 2.7 GHz
RAM	32 GB DDR5
GPU	NVIDIA RTX 3060, 6 GB
Software	Python 3.11, TensorFlow 2.16, PyTorc h 2.2
Operating System	Windows 11 (64-bit)
Validation Method	10-Fold Cross Validation

This experimental procedure as such offered a testing platform to AI-enabled precision cultivation models. The methodology synthesizes both benchmark FAOSTAT data and the simulated sensor inputs of the IoT and introduces an overview of a realistic framework capable of supporting real-time agricultural decision-making and monitoring of both local and global performance.

IV. RESULTS AND DISCUSSION

Our results were obtained through real-time data collection that enables agriculture predictions and decisions in real-time, as well as mathematical simulations that use graph neural networks to provide empirical analysis. Crop experiments use scientific principles, practical experience, and technological solutions, which lead to the design of the proposed model and the development of multidisciplinary study in science and technology. Through the collaborative effort with Russia, agriculturalists from both nations will benefit from real-time crop tracking and surveillance. The aggregate accessibility will be the focal focus of this transformation with Russia, employing AI platforms and mobile applications to engage a broad spectrum of agricultural economists, farmers, environmentalists, and researchers, among others. Productivity can be improved for making informed in-field decisions according to PF.

Feedforward ANN, k-NN, and NB, were used in experiments requiring the training curve to determine which training rate takes place during ML. Weighted mean recall, weighted mean precision and accuracy were employed for error detection. The data is derived from 30 borings in the Inkai's uranium deposits. The ANN algorithm surpasses all other algorithms. This study enhances the framework by using FAOSTAT and modeling IoT sensor data to evaluate model scaling in precision agriculture. The learning curves experiment evaluated Feedforward ANN, Naïve Bayes, and kNN models based on accuracy, weighted precision, and recall measures [13].

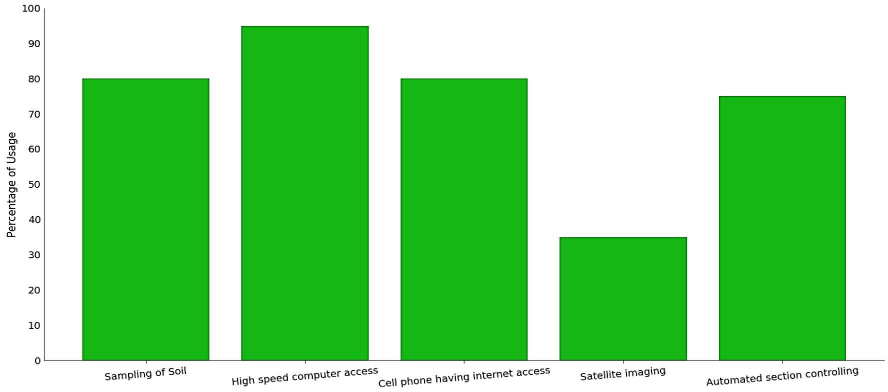

Fig 2. Application of PA Technology.

The findings of this research will meet international standards and is intended for advancement of PF advancement for the use of agriculturalists across the world. The project relates to agriculture, including knowledge transfer and predictive farming. Technology outputs play a role in capitalizing on the shift to personalized deep learning. The new reality takes it also to a quantitative evaluation of all farming – farming processes based on instantaneous data realization considering the spurt in agricultural involvement. PA technology has been used in diverse fields. Some of the industries where this technology has gained popularity are soil sampling, high-speed computer access, internet-enabled mobile phone, satellite imagery, autonomous section control, etc. **Fig 2** shows how PF is used in different sectors.

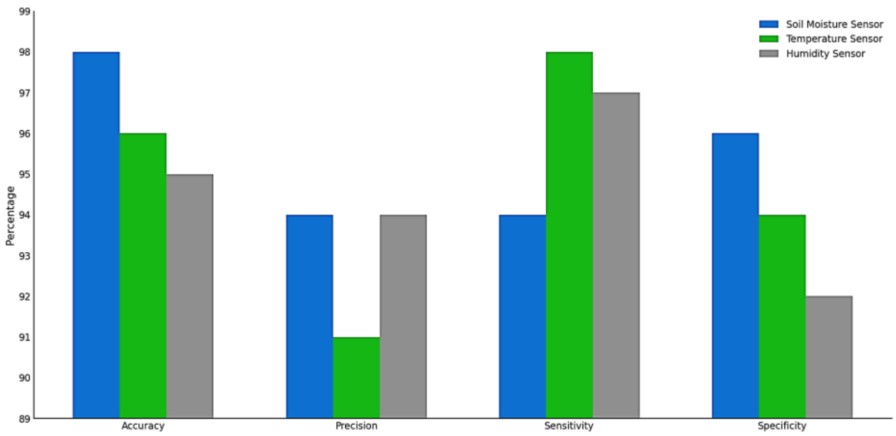

Fig 3. Assessment of IoT Sensor Performances.

Different types of precision agriculture technologies give people the power to use the knowledge of research to develop many variables such as real-time, weather, soil type, and computers. In addition, weather changes, greenhouse gas emissions, wastes, poor soil conditions, and inadequate weather conditions are tackled using PF methods. The PA plays a vital role in observing the state of a natural disaster and its impact on production [14]. Additionally, diverse sensors are employed inside the IoT framework to assess the nutrient and soil composition of PA. For a variety of IoT sensor data, the results of accuracy, precision, specificity, and sensitivity are derived from false negative, false positive, true negative, and true positive events, as shown in **Fig. 3**. Multiple sensors are employed for this experiment, such as humidity sensor, temperature sensor, and soil moisture sensor. They are employed in IoT sensors to assess the dependability of PF. It discloses the surveillance of harvests to advance PF with improved dependability and security.

In pattern recognition, it is essential to choose a suitable classifier to get accurate and reliable predictions. Evaluating techniques like NB, kNN, RF, and proposed technique through accuracy can yield results to show the effectiveness of the technique. This study used FAOSTAT [15] as a benchmark dataset for the classification evaluation of precision framing. The Food and Agriculture Organization of the UN administers a database called FAOSTAT. For PF analysis, farmers are recommended to evaluate fertilizer use, crop production, land use data as it provides various agricultural data. FAOSTAT provides accessibility to global farming statistics, such as livestock production, crop production, land use stats, food records, trade, fertilizer consumption stats.

Users are able to download and explore data, generate visualizations and reports, create custom queries. FAOSTAT collects tons of data and information related to agriculture and is a reference tool for many academic, policymakers and practitioners across the world. FAOSTAT allows one to look up world agricultural trends, crop performance, production patterns, and to make informed decisions on PF. Standard situations found in PF form the foundation of the FAOSTAT dataset. Soil characteristics, weather conditions, crop specifications and many more are included [16]. **Fig 4** compares the accuracy of various classification methods.

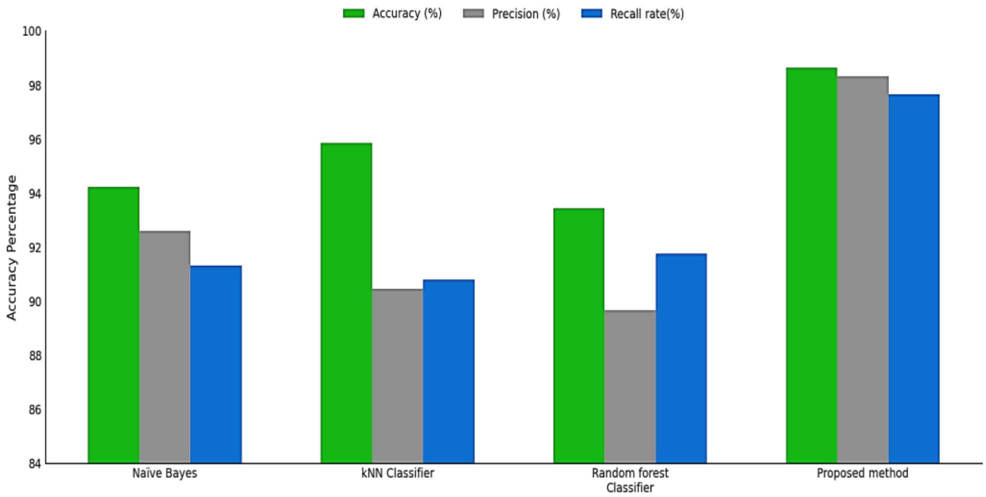

Fig 4. Comparison of Classifiers and Accuracy for PF.

The NB classifier is widely employed in various fields because it is oriented on the independence of features, as evidenced by the comparative study utilizing the FAOSTAT benchmark dataset. Rapid training and prediction durations are attainable. It may, however, struggle with complicated relationships between factors. kkNN is a non-parametric classifier which classifies a sample oriented on its neighboring samples. The number of neighbors (k) greatly influences the accuracy of the method. KNN is simple but computationally expensive on larger datasets. The random forest is a classifier that consists of many decision trees with the objective of improving accuracy and dealing with complex interactions. It shows happy overfitting and understands big data sets. The model transparency could be reduced due to its ensemble condition.

The proposed approach uses some PF-based process and surpasses many savvy classification methods with a recall, precision, and accuracy of 97.65, 98.32, and 98.65, respectively, for grouping analysis of PA through FAOSTAT benchmarking datasets. The classification performance and accuracy of the proposed method are better than those of the classifiers mentioned above. Assessment of the proposed method helps examines whether this method is efficient and competitive as this method explores existing literature on AI, ML, and IoT to boost PF [17].

Fig 5 shows that, in addition to accuracy, the time required for model classification and construction is a crucial metric for PF implementation. The visual depiction indicates that the NB core probabilistic approach frequently leads to rapid model development and prediction durations. The computational cost is less as it calculates the probability based on the independence of features. Yet, model creation can still take longer, depending on feature engineering or data collection. Making a kNN model is easy because it only needs to keep training data saved. Making a random forest model might be slower than building a naive Bayes and kNN model due to making so many decision trees. Speed at which the approach can build systems and make categorization decisions will be influenced by particular algorithms and methods employed in the suggested approach [18].

The NB classifier works on a number of independent features in order to predict multi-class or binary output. The NB Trainer Node generates a frequency element that it uses to train sets for classifying problems. To derive the posterior probability for the two groups, we resort to the frequency table and apply the rule of Bayes, as the appearance of the new character is independent. Consider the present characteristics where data is missing.

However, the missing attribute will not be considered for the algorithm calculations. This means likelihoods for all of the missing attributes are normalized and it gives actual probability to each of the classes. It is possible to convert continuous variables using some methods, like Naïve Bayes. Supervised discretization or kernel density methods are used to characterize numerical.

Priya, Ramesh, and Khosla [19] analyzed the NB technique's use for forecasting crop yield as per the parameters of different crops. Researchers evaluated the efficiency of Naïve Bayes for massive data sets of climate data, soil properties and farming practices. The research study sheds light on how Naïve Bayes model can be useful in predicting the crop yield correctly across various regions and different types of crops. Rashid et al. [20] developed a Naïve Bayes for particular dataset which had a success rate of 95% in predicting yield using area and production as the feature among other parameters. This high degree of accuracy shows to what extent the model can manage the properties of our data.

The model building and category implementation times crucially might be competitive when the offered solution manages to include the use of technologies of high quality: IoT, ML, and AI. The conduction of a study during which the build times of NB, kNN, RF and the proposed method, as well as classification run times will be compared will permit the test of their computational efficiency and their feasibility in real-time PF applications. This is really superior to the standard classifiers in PF since it runs in 0.23 seconds and it is highly accurate.

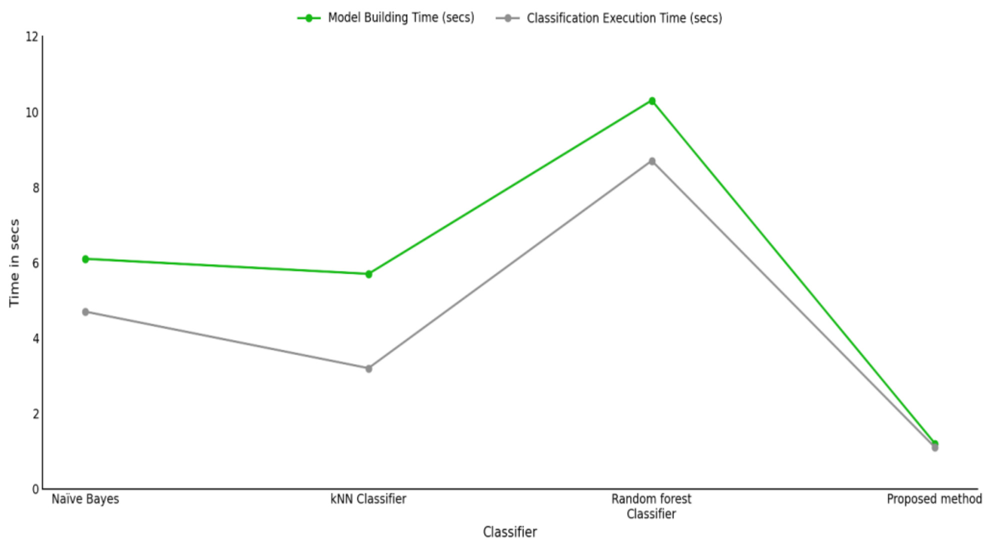

Fig 5. Comparison of Classifier and Execution Time for PF.

V. CONCLUSION

Combining AI data improves predictability and efficiency of precision farming systems. It allows instantaneous monitoring of climate, crop, and soil dynamics. According to test results, the ANN has always been at the top of the most tested models, and the proposed GNN proves that these methods are the most suitable in developing adaptive agricultural analytics. Our results facilitate the development of smarter agriculture by providing real-time sensing, interoperability of data, and guided decision-making. However, future research should look into improving the model and include satellite images. In addition, autonomous drones should increasingly be used to collect data. Edge computing should help bring on-board decentralized AI computation at the scale of a farm. Lastly, the exchanges of data and transfers of knowledge should be boosted across borders through extending international partnerships such as the current relationship with Russia, which will eventually lead to healthy food security and sustainable agriculture output in the world.

CRediT Author Statement

The authors confirm contribution to the paper as follows:
Conceptualization: Amelia Maria Laura and Minu Balakrishnan; **Methodology:** Amelia Maria Laura; **Data Curation:** Minu Balakrishnan; **Writing- Original Draft Preparation:** Amelia Maria Laura and Minu Balakrishnan; **Visualization:** Minu Balakrishnan; **Investigation:** Amelia Maria Laura; **Supervision:** Minu Balakrishnan; **Writing-Reviewing and Editing:** Amelia Maria Laura and Minu Balakrishnan; The author reviewed the results and approved the final version of the manuscript.

Data Availability

The datasets generated during the current study are available from the corresponding author upon reasonable request.

Conflicts of Interests

The authors declare that they have no conflicts of interest regarding the publication of this paper.

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Competing Interests
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